Mapping Learning Aids and Introducing Learning Styles as a Moderator

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Abstract

There is evidence that different learning styles require diverse modes of communication. Based on 377 completed standardized questionnaires this study contributes to this field of research. To test the relation between learning aids and learning styles double coded data is analyzed by applying a multiple correspondence analysis. Further, impacts of extrinsic motivation, self-efficacy, subject-value, and the usefulness of an e-learning system on actual success (grades) are examined. Furthermore, differences between learning styles are revealed by applying a structural equation model. Results show that for a marketing-students population various sources need to be provided to cater diverse learning styles. It is also shown that the examined aspects impact on students’ actual performance differently depending on their learning styles. Implications and future study suggestions are provided.

1. Introduction

Imagine scoring a goal with your eyes closed or hitting the bull’s-eye when playing darts with a blindfold. In both cases, you cannot see your target and therefore, it would be nearly impossible to hit it. Transferring this as a metaphor to business means doing business without knowing the target market, the subset of people interested in your product. Such an approach of acting without knowledge about consumers’ wants and needs might ruin a business. As an entrepreneur, it is essential to identify your customers and understand their requirements as precisely as possible. For most products and services a “One-Fits-All” marketing-strategy is not appropriate. Enterprises need to differentiate and tailor their offers to gain competitive advantage [3].

Universities can and should be seen as enterprises with several stakeholders, and in some ways students are their customers. Consequently, universities need to identify students’ needs. Looking at learning styles is a possibility to identify individual needs of students which might allow for outstanding success and in turn positively influences a university’s reputation.

According to literature in the field of education individuals learn differently and no single didactical strategy is best for all students. Thus, students will achieve learning goals more efficiently, if pedagogical procedures are adapted or accommodated to their individual needs [26]. Tailored teaching materials seem to be even more important in an online environment not allowing for face-to-face interaction, so that the students feel engaged [82].

Turning the attention from a teacher-centered to a student-centered approach has several advantages, which have been discussed by Ngeow [59]. Among the main benefits shown are that people who are aware of their learning style may use learning opportunities more efficiently. People can grasp information quicker if they are provided with learning environments that enhance their learning preferences. Finally, people can adapt better to new learning styles if guidelines are given which allow people to practice the new learning modality.

In a blended learning situation a whole range of teaching aids can be used to meet the needs of all learning styles. Some materials might be more easily provided online by utilizing available communication modes such as podcasts, slides, or simulated exercises [50]. To the best knowledge of the authors there are no studies investigating the relationship between the perceived importance of learning materials and learning styles. The study at hand aims at contributing to this gap. Further, the impacts of extrinsic motivation, self-efficacy regarding learning performance, value of the subject marketing, and the usefulness of the e-learning system on actual performance are examined. In doing so, differences between learning styles are revealed. The crucial questions investigated are the following: Do students access diverse combinations of learning materials based on their learning styles to learn marketing? Do different learning styles have similar learning patterns regarding materials accessed? Additionally, the question whether diverse aspects impacting on the
actual success (= grade) of learning differ between learning styles is examined.

2. Theoretical background

The idea that people gather information differently already dates back to the ancient Greeks [85]. Differences concerning information processing are elaborated in diverse learning theories. An overview of theories and models is provided by Cassidy (2004) and Coffield et al. [12] who identified 71 different models of learning style in a meta-analysis. These models can be classified into cognitive-centered, activity-centered, and personality-centered approaches [e.g. 12, 17, 18, 67]. Generally, diverse cognitive processing modes are referred to as learning styles. The concept of learning styles is defined as "an individual's natural, habitual, and preferred way(s) of absorbing, processing, and retaining new information and skills" [68] (p. viii) or as "educational conditions under which a student is most likely to learn" [77] (p. 16).

2.1. Learning style inventories

Learning styles are investigated in diverse fields of research such as management, website design, or very often in an educational context. Many concepts and methods used to examine learning styles are borrowed from psychology. Due to the variety of studies conducted and the complexity of the topic Cassidy [11] attempts to bring together central issues and to clarify ambiguous areas. However, there is no consensus on pertaining to one single, best measurement of learning styles [12]. Many different learning style measurements can be identified such as the Learning Style Inventory (LSI) by Kolb [49], the Learning Style Questionnaire (LSQ) by Honey and Mumford [41], the Felder-Silverman learning style model [27], the VARK model by Fleming and Mills [28], or the C.I.T.E. Learning Style Inventory developed by Babich, et al. [4], just to name a few.

Most of the inventories include the so-called Visual-Auditory-Kinesthetic learning style model, usually abbreviated VAK [16]. It covers three techniques of sensory learning: visual (sight), auditory (sound), and kinesthetic (touch or motion). The visual learners can further be categorized into visual-linguistic learners, who learn most efficiently through reading and writing tasks, while visual-spatial learners prefer graphs, illustrations, color coding, and other visual aids. An auditory learner can best absorb information by having a conversation with someone, listening to podcasts, or to a lecturer. A kinesthetic learner performs best when encouraged to be active; they like experiments and hands-on-trainings [62]. The C.I.T.E. Learning Style Inventory not only concentrates on VAK, it also incorporates working conditions and expressive preferences. Working conditions focus on whether students prefer collaborative or individual working, while expressive preference considers if students fancy oral or written communication. Furthermore, the C.I.T.E. questionnaire splits up VAK dimensions leading to nine different learning styles, namely visual language-, visual numerical-, auditory language-, auditory numerical-, tactile-kinesthetic-, social-individual-, social-group-, expressive-oral-, and expressive-written style [4, 78].

Although in theory it is possible to distinguish between different learning styles, learning styles are not dichotomous; black or white [25]. Instead, most people use a mixture of available styles [84]. The C.I.T.E. Learning Style Inventory for instance further refines each of the nine learning styles to be the “Major”, “Minor”, or “Negligible” learning mode of a specific person.

2.2. Matching learning- and teaching styles

Learning and teaching style should be a dialog. In several studies researchers point out that a mismatch of learning and teaching style leads to poor achievement [e.g. 29, 35, 70]. Giles et al. [34] demonstrate that there is a need to balance between teacher- and student-centered activities in class and that students are aware of what is the best activity for their own learning style. According to Keefe [46] knowledge about learning styles allows better and more rational instructions to assist and motivate students.

All students have their own preferred combination of learning styles; learning strengths and weaknesses. Teachers have to identify these styles and need to adapt their teaching styles accordingly. A mismatch between teaching and learning styles causes learning failure and frustration. A study on students in Hong Kong shows that 72% felt upset, 76% said they are affected in a way that they hardly can concentrate, they are bored, feel stressed, or even want to drop the course [62]. There is evidence that students’ attitude towards a subject is more positive if learning styles are considered [27]. Therefore, teachers should create learning environments which stimulate students to take responsibility for learning [81]. However, successful classroom performance also depends on individual characteristics of students such as being internally motivated, the capability of setting goals, or the desire to attend class regularly [32]. Locus of control, conscientiousness, anxiety, age, cognitive ability, self-
efficacy, valence, and job involvement are further characteristics influencing learning performance [14].

Research shows that if teachers can give students instructions in a way which matches their learning styles, learning success usually improves significantly [22, 61]. Furthermore, students’ motivation will be enhanced [10]. Thus, increased awareness of styles should be part of teacher training, development, and assessment [62].

3. Conceptual framework

From the previous sections we learned that students need to take responsibility for their own learning [81] but teachers should reveal learning styles, explain the rational and benefits behind the styles, and adapt teaching strategies to reduce learners’ resistance [62]. Diverse learning styles demand for various modes of communication. The visual language type gets more out of textual representations like words in books, on the chalkboard, on charts, or on the screen. This also means that s/he may even write down words that are given orally, in order to learn the content by seeing it. The visual numerical learner concentrates on numbers and understands math facts more likely if s/he can look at the issue. An auditory language learner is someone who learns from hearing words spoken. Therefore, if there is no possibility to visit a lecture and study material is only available in written form, auditory learners often vocalize or at least move the lips while reading, particularly when studying new material. Remembering telephone numbers or historical dates is easy for auditory numerical learners. Such a learner can solve math problems without her/his math book because s/he can calculate or rethink problems in her/his head. Tactile-kinesthetic learners benefit most, if they are totally involved. Hence, learning by doing is a good method to teach this group. Referring working conditions the measurement instrument distinguishes between social-individual and social-group learners. While the social-individual learner increases recognition of facts when s/he can study on her/his own, the social-group learner assess other opinions and group interaction as important. Articulation preferences are the last distinction made. A student showing an expressive-oral learning style feels more comfortable taking oral tests and s/he usually speaks fluently, and clearly. Putting thoughts on paper is preferred by students with an expressive-written style [78]. Due to the different needs of these learning styles, they demand for learning aids provided in various modes.

H1: There is a relationship between preferred learning-style and learning aids accessed.

Extrinsic motivation. “Motivation is what stimulates students to acquire, transform and use knowledge” [38] (p. 62). Motivation plays an important role during the learning process [43] and directly effects learning outcomes [e.g. 48, 51]. Students are intrinsically motivated when they engage in learning activities for their own sake. However, the desire to learn as an end in itself is inhibited or even destroyed by extrinsic rewards, incentives like school grades [15, 31], and social demands like parental expectations. Hence, most of the activities people do are done for its instrumental value; as a means to an end. Falling short of one’s grade goals or fears regarding parental sanctions may intensify one’s concentration on doing better [71].

H2: Extrinsic motivation has a direct positive effect on success (grade).

Self-efficacy. Social cognitive theory stipulates that self-efficacy strongly impacts on performance [7]. Student self-efficacy, which is a students’ positive self-perception of competence, is examined heavily in previous studies [e.g. 40, 64, 65]. It is shown that self-efficacy stimulates the use of effective learning strategies. Further, there is evidence for a correlation between self-perceived competence and greater interest in carrying learning tasks [9, 65, 73]. The direct effect of self-efficacy on learning outcomes is confirmed by a more recent study by Lim [51]. Meta-analysis regarding previous research focusing on the impact of self-efficacy on performance are provided by Colquitt et al. [14], Locke and Latham [53], and Staijkovic and Luthans [75].

H3: Self-efficacy has a direct positive effect on actual success (grade).

Value of the subject. Perceived subject value is about a person’s interest in a subject regarding their short- and long-term goals, which includes considerations pertaining to future profession. Value in this sense is researched in the context of expectancy-value theory [23, 24]. Studies shed light on the fact that students with interest and high task values are prepared to use more effective strategies such as task monitoring and self-regulation [2, 63, 65]. Ames [2] noted that students are more likely to use effective strategies when tasks are perceived as worthwhile and challenging. They also pay more attention to improve their own educational attainment rather than comparing their own performance with others. Students evaluating the subject as worthwhile are more likely to succeed [47, 52].

H4: Value regarding the subject has a direct positive effect on actual success (grade).
Usefulness of the e-learning system. Usefulness is the degree a system is able to assist individuals [20] in their objective to learn for a specific subject. In other words a system which is believed to be useful positively impacts on the performance level [60]. In a blended learning environment, students have no choice whether they want to use the system or not because one part of such a seminar is conceptualized to be accessed via the e-learning system. Therefore, it seems to be even more important to include the perceived usefulness of the system and its impact on the learning performance.

H5: Perceived usefulness of the e-learning system has a direct positive effect on actual success (grade).

Learning styles. There is evidence that science students have a stronger preference for learning in groups while humanities students’ prefer auditory and individual learning styles. Older students like learning by doing and therefore favor the kinesthetic style [62]. Marketing students are rather visual than auditory, especially male students [56]. Thus, previous literature revealed differences concerning motivation or system usefulness for instance between men and women or between various cohorts. However, due to a lack of theoretical foundations study results dealing with demographics are inconsistent [14]. The present study goes one step further by not investigating differences based on demographic matters but on individuals’ preferred communication modes to learn new issues; their learning styles. A paper published by Neuhauser [58] analyzes the direct effect of learning styles on performance, but only little or no impacts on final grades are exhibited. These results might be due to the fact that learning styles moderate constructs impacting performance rather than directly influencing success.

Due to these issues the authors propose the following hypotheses in a marketing context:

H6: Different learning types vary regarding the impact of a) extrinsic motivation, b) self-efficacy, c) value of the subject, and d) usefulness of the e-learning system on actual success (grade).

3. Methodology

Previous literature suggests to base the decision for a specific learning style inventory on three major facets: Appropriateness and soundness of the conceptual base, research data supporting it, and practical considerations [44]. The C.I.T.E. Learning Style Inventory [4, 78] was chosen for this study because it describes the learning styles in more detail than other questionnaires do; without exhausting participants with too many questions. Comprising 45 questions C.I.T.E. is among the most parsimonious measurement instruments in this context. Moreover, the instrument not only detects learning styles but compared to other popular learning style questionnaires, the C.I.T.E. inventory identifies preferences for both, perceptual and social domains. The social domain seems to be especially important for the study at hand because the e-learning-system also offers features allowing for interaction between students. Another issue for choosing C.I.T.E. is that it was developed for revealing learning styles of adults [44, 83] which are also the focused research subjects of the present study. Further, reliability and validity of learning style instruments have been questioned in critical reviews [19, 74]. However, two studies by Babich et al. [5, 6] show satisfying levels of both for the C.I.T.E. instrument.

Regarding the perceived importance of 15 different modes of learning respondents had to allocate 100 points proportionally. In detail, these are the following: The textbook of the course, additional online-notes to the subject, the slides of the lecture, as well as attending the lecture. Studying from own notes, the usage of notes or summaries produced by colleagues, studying together with colleagues, are further modes. Online-exercises providing automatic feedback (e.g. response-accuracy, hints to reading assignments, and further explanations), online-sample-exams, an online-glossary, FAQs, the possibility to post or answer
questions in discussion forums, and the ‘article of the week’ also had to be rated.

Additionally, the questionnaire included two items to measure ‘extrinsic motivation’. For ‘self-efficacy’ regarding learning, ‘subject value’, and ‘system usefulness’ four items are included for each latent construct. All these items are borrowed and adapted from previous literature [20, 21, 66]. As an outcome measure grades achieved by the students in the marketing course are added to the dataset after the survey was conducted.

After the pre-test the self-administered questionnaire was distributed online; right after the marketing exam before people got their degree/grade. A reminder asking people for participation was sent one week after the first transmission.

4. Analysis

Correspondence analysis (CA) is an exploratory multivariate technique and looks for structure in a set of data. CA is a worthwhile technique to be used to examine categorical data. Generally, it is useful because categorical data is very common in many fields doing questionnaire-based surveys. CA plots cross-tabulated data and allows for grasping patterns of numerical frequencies easily. For a detailed description of CA see Greenacre [37]. Insights for which purposes CA can be used are also given by Joseph F. Hair et al. [45]. Although CA itself is a fairly well-known method, there seem to be hardly any applications in the field of educational research where subjects and attributes are jointly displayed. The detected learning styles are used as explanatory variable in the CA. Based on the 45 items the nine C.I.T.E. learning styles are estimated following the suggested procedure by Babich et al. [4]. An important aid in interpreting the results is the possibility to include supplementary points. In the present study the perceived importance of 15 different teaching aids provided to study marketing were included as supplementary points in our case. In doing so the CA-package in R is used [36]. There are several ways of recoding continuous data in a form suitable for CA. The usual approach of recoding continuous or preference data is a so-called “doubling” of the table. The idea behind is to allocate two complementary sets of data, where only the endpoints of the bipolar scale are displayed in a multiple CA [37, 79].

The amount of learning styles (without considering tactile-kinesthetic learning, working conditions, and expressive preferences) based on the responses given, has to be reduced to get a manageable amount of styles for multi group analysis. Thus, to reveal learning style mixtures on an individual level the Typology Representing Network (TRN–32) toolkit, which applies the neural gas algorithm [54], was used to perform a cluster analysis [55]. The TRN clustering approach favored a three segment solution, with a wSSI of .33. The uncertainty reduction over 50 replications yields 94.1%. Regarding the size of the segments the groups are nearly evenly divided with 33.7%, 32.4%, and 34.0%. In the following the learning style types are described briefly and concise segment-labels are dedicated.

Visual-linguistic learner (33.7%): This segment fancy any kind of written material they can learn from, and they can grasp mathematic facts quite well, if facts and figures can be learned from written documents.

Visual-spatial learner (32.4%): Learning from visual aids such as pictures, illustrations, textual representation, or other depicted information is preferred by this group of students.

Analyzer (34.0%): This group more or less can be perceived as ‘mathematicians’, because their major learning styles are visual numeric and auditory numeric. Beside this affinity for numeric information the group can also grasp information put differently. However, visual language and auditory language are only the minor learning styles of ‘Analyzers’.

The individuals’ segment membership is used as a grouping variable in the covariance based structural equation model (CBSEM). The CBSEM is tested applying Mplus, a second generation SEM software tool [57]. Mplus provides estimators not requiring normally distributed and metric data. For the present study the robust estimator MLM is used [72]. Only items loadings in excess of .73 are included in the measurement model. Examination of the local fit measures shows that reliability is in accordance with the levels recommended by Fornell and Larcker [30]. Average variance extracted (AVE) values are >.65 and composite reliability (CR) >.80 and thus are well above the suggested thresholds of .5 and .7 respectively. Discriminant validity is given with squared correlations of the latent variables not exceeding AVE. By analyzing latent variable correlations construct validity is proofed to be at a satisfying level with correlations between .01 and 0.39. Inspection of the items secured face validity. Pertaining to multi group comparison the notion of Baron and Kenny [8] is followed. Further related
aspects are discussed in a book by Aguinis [1]. Following recommendations by previous authors four models are tested; first, the overall model without considering any groups; second, the model is estimated again for the three groups (Visual-linguistic learner, Visual-spatial learner, Analyzer) applying the multi group analysis procedure provided in Mplus.

5. Results

5.1. Sample description

After data cleaning the sample consists of 377 usable questionnaires. There are more female (60.2%) than male respondents. On average students doing the first marketing course at the university are 21.73 years old. 84.4% are German native speakers. Regarding second-chance education, nearly one third used to work before entering the university (31.3%). About the same amount of people work part time alongside attending university courses (31.8%), 8.8% have a full time job, and more than half do not additionally work but focus on their studies only. 76.1% of the respondents consider themselves as highly skilled regarding Internet usage. Finally, on a grading system of 1 (=excellent) to 5 (=failed) people passed the marketing course with a grade of 3.22 (=satisfactory) on average; 35.1% achieved excellent or good.

5.2. Mapping learning styles and sources

The CA analysis proposes either a two- or a three-dimensional solution. According to the ‘scree test’ one should stop interpreting dimensions when the curve makes an ‘elbow’ [39]. In our case the ‘scree test’ favors a two-dimensional solution. The second criteria for deciding on the amount of dimensions, the Kaiser criterion, suggests excluding dimensions with eigenvalues below 1.0 [33, 45]. The eigenvalue of the third dimension is 1.2. Due to the ‘scree test’, and the fact that the third dimension only accounts for about 10%, a two-dimensional solution is preferred.

The first and the second dimension jointly explain 53.7% of total inertia (variance). The first dimension of the multiple CA accounts for 31.1% of the total inertia. Figure 2 shows that this dimension clearly separates students preferring auditory learning styles (language and numeric), group interaction, and oral expression, from students, who do not like these styles. Further, Figure 2 depicts the perceived importance of the learning materials as supplementary points. Auditory learners prefer online learning aids such as FAQs, the possibility to post or answer questions in discussion forums, online-homework, or “articles of the week”. The traditional way of learning like attending a lecture is also valued highly by these students.

The second dimension, which explains 22.2% of the total inertia, is dominated by the visual language learner on top of the plot, while auditory language learners or students not being visual and not favoring individual learning can be found on the bottom. Exercises and own notes are important sources for the visual language learners. Sample-exams are equally used by all styles; such an average usage of learning aids is not shown in the plot to clear up the picture.

5.3. Structural equation model

Overall model: Fit indicators show that the model fits the data well; with a TLI of .954 and a CFI of .965 [42]. The RMSEA and the SRMR are at a satisfying level of .057 and .040 respectively. Standardized coefficients of the model show that ‘self-efficacy’ has the strongest effect on the grade achieved with a $\beta$-coefficient of .568 ($p<.001$) followed by ‘e-learning system usefulness’ ($\beta$=.130; $p<.002$). ‘Value of the subject’ has a negative impact on the grade ($\beta$=-.190; $p<.001$) and ‘extrinsic motivation’ does not appear to be significant.

Moderator – Learning styles: As already mentioned above a multi group analysis is carried out following suggestions by Baron and Kenny [8]. The group membership whether a marketing-student is a ‘Visual-linguistic learner’, a ‘Visual-spatial learner’, or an ‘Analyzer’ is stipulated by the TRN cluster analysis, presented earlier in the analysis section. The estimation of four models ensures that not the measurement error is responsible for changes in $\beta$-coefficients but hypothesized effects [76]. The following Table 1

![Figure 2. CA plot of learning styles and learning materials](image)
displays the estimates; figures in brackets are not significant.

In order to reveal if differences between the three groups of learning styles are significant the tolerance intervals are inspected. Table 1 indicates that there are highly significant differences between all three groups (G1:G2:G3) regarding extrinsic motivation. Self-efficacy shows a significant difference between ‘Visual-spatial learner’ and ‘Analyzer’ (G2:G3). There are no significant differences for the relationship between ‘subject value’, ‘system usefulness’ and ‘grade’. However, this is of minor interest because the ‘subject value’ path for ‘Analyzer’ is not significant and ‘system usefulness’ neither has a significant impact for the ‘Visual-spatial learner’ nor for the ‘Analyzer’. The impact of extrinsic motivation turns out to be negative for the ‘Visual-spatial learner’ and the ‘Analyzer’ (β = −.153, p<.041; β = −.205, p<.016) but not for the first group (β = −.141, p<.012). For the first group ‘self-efficacy’ has the main impact (β = .624, p<.001), this impact is even stronger for the second group (β = .726, p=.001). ‘Self-efficacy’ is also the main driver for the third group (‘Analyzer’) but less strong (β = .399, p=.001). ‘Subject value’ has a negative impact for the first two groups but turns out to be not significant for ‘Analyzer’.

<table>
<thead>
<tr>
<th>Path estimates</th>
<th>Overall model</th>
<th>Visual-linguistic learner (G1)</th>
<th>Visual-spatial learner (G2)</th>
<th>Analyzer (G3)</th>
<th>Significance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Extrinsic motivation → Grade</td>
<td>-.047</td>
<td>.141*</td>
<td>-.153*</td>
<td>-.205*</td>
<td>G1:G2:G3</td>
</tr>
<tr>
<td>Self-efficacy → Grade</td>
<td>.568</td>
<td>.624*</td>
<td>.726*</td>
<td>.399*</td>
<td>G2:G3</td>
</tr>
<tr>
<td>Subject value → Grade</td>
<td>-.190</td>
<td>-.144*</td>
<td>-.265*</td>
<td>(-.088)</td>
<td>n. s.</td>
</tr>
<tr>
<td>System usefulness → Grade</td>
<td>.130</td>
<td>.114*</td>
<td>(.085)</td>
<td>(.119)</td>
<td>n. s.</td>
</tr>
</tbody>
</table>

* Significant at a 0.001 level.  * Significant at a 0.05 level.  * Significant at a 0.07 level.

6. Conclusion and implications

First, findings from this study show that learners with different learning styles indeed use other modes of learning. Thus, previous research is confirmed [78]. Only sample-exams have the same importance to all learners and are used equally by all learners to get prepared for the exam.

Second, extrinsic motivation has no significant impact on achievement in the overall model, but it has a negative impact on the success for ‘Visual-spatial learners’ and ‘Analyzers’. Only the ‘Visual-linguistic learner’ turns out to be positively influenced through incentives. Here a deeper insight into the characteristics of these learners and the differences within the extrinsic motivations would be necessary. Due to the fact that extrinsic motivation might be a good grade or the access to an interesting course for one student, while for another student it is the parents’ punishment (e.g. no further financial support). This might put pressure on a student [71].

Third, the positive effect of ‘self-efficacy’ on learning outcome can be confirmed by the results. There is evidence that doing well causes positive feelings like pride, which in turn increases their enthusiasm for learning. Doing well reduces worry about failing, so students feel free to explore what is most interesting. Being successful stimulates them to study more, and the more they learn, the more interesting the material is likely to become [15], which in turn has an effect on the value of a subject.

Forth, the ‘value of the subject’ has a negative impact on the grade. A reason for this negative impact might be that students rating the subject as very important are confronted with greater fear to fail. Hence, exam nerves could have a high influence and therefore, test anxiety should be included in a follow-up study. Another explanation might be that students evaluating the subject high are very frustrated by only being tested based on a multiple-choice-test at the end of the course, which was the format of examination.

Fifth, the usefulness of the e-learning system in general has a positive impact on the performance level which supports other findings [60]. Looking on the effects of the different learners more closely this influence can only be found for ‘Visual-linguistic learners’. Qualitative interviews or ethnographic approaches would allow for further insights.

Sixth, moderating effects of learning styles on the performance (grade) are detected as hypothesized. These findings support the assumption that learning styles moderate constructs impacting performance rather than directly influencing success as analyzed by Neuhauser [58].

All presented results suggest a number of implications for instructors. The proved importance of different learning styles and their effect on achievement, demands for the necessity of being aware of the learning styles, this is true for both students and faculty.
Faculty not only has to provide different teaching materials but also diverse instructions for each learning type. CA visualizes the relationships. Respective materials and instructions need to be integrated into an e-learning system as well. Appropriate guidance will enhance the usage and consequently the level of performance of diverse types of learners. This seems to be even more important in the light of the increasing mobility and the strategic importance of internalizing lifelong-learning in the society, which demands for a larger amount of well-designed e-learning systems. Learning style tailored systems could support individual learning developments. Research has shown that learning styles can change and develop over time as learners build up knowledge and experience through learning [13, 69]. Due to the changes of learning styles over time a longitudinal study might be worthwhile.

Furthermore, students would benefit even more if a learning style questionnaire is integrated in an e-learning system to allow students to identify their strength and weaknesses immediately. Learning style adapted instructions could then be prompted to the students after finishing the test. Such a match of learning and ‘teaching’ style would improve attitudes towards a subject as suggested in literature [27]. An interesting by-product of the study is that in accordance to Morrison et al. [56] the finding that marketing students are rather visual than auditory is confirmed.

It should be mentioned, that the study presented used a convenience sample only, which resulted in an overrepresentation of excellent students. However, there is no argument that these students are significantly different from other marketing-students regarding their style of learning. Still, further investigations on another cohort are needed. Finally, another problem is that the sample got rather small for multi group comparisons.

References


[50] Learn@WU, Das Projekt Learn@WU. Retrieved 15.03.2010 from https://learn.wu.ac.at/about/projekt


[54] T. M. Martinetz and K. J. Schulten, "A "Neural-Gas" Network Learns Topologies", in Artificial Neural